Performance Evaluation of popular pre-trained CNN Models on Plant Disease Detection: A Case Study on Mango, Guava, Black Gram, and Sugarcane Datasets

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Abstract

Crop production worldwide is adversely affected by various plant diseases, highlighting the importance of disease identification and classification. Traditionally, this process relied on specialists and experts, which proved to be time-consuming and cumbersome. However, advancements in machine learning and deep learning have revolutionized disease classification. Convolutional Neural Networks (CNNs), particularly in the domain of plant leaf diseases, have demonstrated remarkable success. This paper focuses on training pre-trained models using three distinct plant leaf disease datasets—Mango, Guava, Black gram, and Sugarcane with varying parameters to identify the most effective models achieving high accuracy. Additionally, the study explores the impact of data augmentation, fine-tuning, and dropout techniques on model performance. The findings demonstrate the effectiveness of transfer learning in plant disease identification, with fine-tuned CNN models achieving remarkable accuracy.

Keywords— *CNN, deep learning, transfer learning, plant leaf diseases*

1. INTRODUCTION

The global population continues to increase, leading to heightened concerns over food scarcity. It is imperative to address this issue by identifying and mitigating plant diseases. Agriculture plays a pivotal role in the livelihoods of millions worldwide, and plant diseases and pests severely undermine crop productivity each year. Consequently, low agricultural output directly or indirectly affects us all. Plant diseases can be caused by two main factors - biotic and abiotic. Biotic factors are caused by pathogens like bacteria, fungi, viruses, parasites, etc. Nutritional excess or deficiency, soil acidity, excess or less sunlight, low oxygen content, etc. comes under abiotic factors [1]. Most plant diseases are caused by pathogens that show mostly on the plant leaves. It is difficult for a common farmer to diagnose the disease just by looking at the leaves therefore a skilled plant pathologist is needed to correctly diagnose the disease. This process is rather time-consuming and wastes the time of the farmer. That is where applications using deep learning and CNN models come into the picture. These can help farmers correctly identify diseases, save cost and time, and increase crop production. As more and more data is gathered and newer and better models are trained on them, we will be able to identify and diagnose diseases early and accurately, which will help the agriculture sector. A lot of crop production can be saved each year, usually lost due to diseases.

2. RELATED WORK

In [2] the authors used a dataset consisting of 1,500 images of lady finger leaves. The images were pre-processed by resizing them to a standard size of 224 x 224 pixels and applying contrast enhancement to improve the image quality. The authors then used a deep learning approach for classification, using a convolutional neural network (CNN) with transfer learning. The authors experimented with various CNN architectures, including VGG16, InceptionV3, ResNet50, and MobileNetV2. They compared the performance of each architecture and found that MobileNetV2 achieved the highest accuracy of 97.67%. To further improve the performance of the model, the authors applied data augmentation techniques such as rotation, shear, zoom, and horizontal flip. They also used dropout regularization to prevent overfitting.

In [3] they have tried to classify banana diseases like black Sigatoka, yellow Sigatoka, bacterial wilt, and dried/old leaves. A CNN network with total generalized variation fuzzy C means (TGVFCMS) was proposed in this paper and compared with other models like Random Forest, decision tree, SVM, and RNN. It achieved an accuracy of 93.45%. They also compared models with/without pre-processing and segmentation.

In [4] authors have classified five different types of mango diseases namely anthracnose, leaf gall, leaf webber, and Alternaria leaf spots. The dataset consisted of about 1200 images. The proposed model was able to achieve 96.675% accuracy.

In [5] the authors used MobileNetV2 and NasNetMobile models of CNN to classify diseases of cassava plants. The dataset used is iCassava 2019. The authors collected a dataset of 4,555 plant leaf images from four different crop plants infected with five different types of diseases. They used several data augmentation techniques, including rotation, flipping, and random crop, to create an augmented dataset with more than 30,000 images. The authors then used transfer learning to fine-tune the pre-trained MobileNetV2 and DenseNet121 models for their classification task. The proposed method achieved an accuracy of 96.84% on the testing set.

In [6] a ResNet50 architecture was used to classify papaya plant diseases namely- leaf curl and papaya mosaic. The average accuracy, sensitivity, and specificity obtained were 85.1%, 90%, and 61% respectively. Anthracnose, powdery mildew, and black spot are three frequent diseases of papaya leaves that are detected and categorized using the suggested method using a convolutional neural network (CNN). A dataset of 1600 photos of papaya leaves was gathered by the authors, and it was divided into training and testing sets. They expanded the dataset and avoided overfitting by using data augmentation techniques like rotation, flipping, and scaling. The pre-trained Inception V3 model was then adjusted by the authors using transfer learning for their classification challenge.

In [7] the authors propose a web-based application called "Farmer Buddy" that uses a convolutional neural network (CNN) to classify cotton leaf images into one of four categories: healthy, bacterial blight, leaf curl, and leaf spot. The authors collected a dataset of 1200 cotton leaf images, which they split into training and testing sets. They then used transfer learning to fine-tune the pre-trained VGG16 CNN model for their classification task. The proposed model was evaluated using various metrics such as accuracy, precision, recall, and F1 score. They reported an accuracy of 96.67% on the testing set, demonstrating the effectiveness of their proposed model in detecting cotton leaf diseases. They also compared their model's performance with other state-of-the-art deep learning models and found that their model outperformed them in terms of accuracy.

In [8] the researchers have tried to classify grapevine leaf diseases. The dataset contains unhealthy leaves affected by Esca disease. They used a custom CNN model with various data augmentation techniques like rotation, flip, shear, zoom, blur, contrast, etc. They were able to achieve a test accuracy of 99.16%.

3. MATERIALS AND METHODS

For the research, we used the Tensorflow framework on Kaggle and the GPU used is GPU P100. In this section, we discuss the datasets, data preprocessing, and different CNN architectures used for training.

3. 1 Datasets

In this work, we have used four different newly published datasets that contain images of plant diseases of mango, guava, sugarcane, and black gram.

a) MangoLeafBD dataset [15]: This dataset contains mango leaf disease images with eight classes of Seven diseases: Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Powdery Mildew, and Sooty Mould. Each category contains 500 images.

b) Guava Leaves and Fruits Dataset [16]: The dataset contains the image of Guava leaves and fruits which are affected along with disease-free that can be utilized to develop an automated system for the researchers to predict the diseases in guava plants. The dataset is comprised of four diseases of guava namely Phytophthora, Red Rust, Scab, and Styler end rot. The disease-free leaves are also attached to the dataset.

c) Sugarcane Leaf disease dataset [17]: Manually collected image dataset of sugarcane leaf disease. It has mainly five categories in it. Healthy, Mosaic, Red rot, Rust, and Yellow disease. The dataset has been captured with smartphones of various configurations to maintain diversity.

d) Black gram Plant Leaf Disease Dataset [18]: The Dataset is having five categories of black gram diseases images Four most common leaf diseases of Blackgram crop are Anthracnose, Leaf Crinkle, Powdery Mildew, Yellow Mosaic & healthy category. The dataset is collected from the cultivation fields at Nagayalanka, Krishna (d.t), Andhra Pradesh, India.

3.2 Data Preprocessing

All the datasets were prepared for training using data preprocessing. In the first step, the image pixels were divided by 255 to normalize them between 0 and 1. This helps to make pixel values consistent across all images and improves the convergence of the network models. The dataset was split into training and test set of ratios 80% and 20% respectively, a further 20% of the training set was used for validation to see how the model performs.

Data augmentation techniques were used to increase the size and variation of the data. Rotation, width shift, height shift, shear, brightness, etc. were used for data augmentation. The Keras ImageDataGenerator class was used to implement the preprocessing pipeline, which made it possible to create augmented images quickly while training. The data preprocessing pipeline's hyperparameters were as follows: the batch size of 64 and maximum epochs of 50 or till the model converges.

3.3 CNN models

Four different CNN architectures were used as the base model in the training namely- MobileNetV2, InceptionV3, Xception, and DenseNet201. These models were pre-trained on Imagenet. Further, a dense layer with ReLU (Rectified Linear Unit) activation and a dropout layer was also added to the base model which is then fed to the output layer with softmax activation function for multiclass classification.

4. RESULTS

Let us now discuss the results we gathered after training various models with and without data augmentation, fine-tuning, and dropout. The base models used are MobileNetV2, Inception, Exception, and Densenet201 which are pre-trained on Imagenet. The metrics used for comparison are accuracy, precision, recall, and F1 score.

In Table 1. We compare the models on the mango leaf dataset. All four models performed fairly well on test data giving very high accuracy even without data augmentation or fine-tuning them. Densenet201 performed the best with 99.75% accuracy and InceptionV3 performed worst with 97.75%. The high performance can also be attributed to high-quality image datasets. The images are clear and there is no background noise. Other metrics like precision, recall, and f1 score metrics are also very high. As evident from Figure 1 we can see that the best model only predicted two images of Gall Midge disease wrong, the rest of the images were successfully classified.

TABLE I. PERFORMANCE METRICS FOR THE MANGO LEAF DATASET

Base Model	Data Augmentation and Fine Tuning	Dropout	Accuracy	Precision	Recall	F1 score
MobileNetV2	No	0	99.5%	1.00	1.00	1.00
InceptionV3	No	0	98.12%	0.98	0.98	0.98
Xception	No	0	98.87%	0.99	0.99	0.99
Densenet201	No	0	99.75%	1.00	1.00	1.00

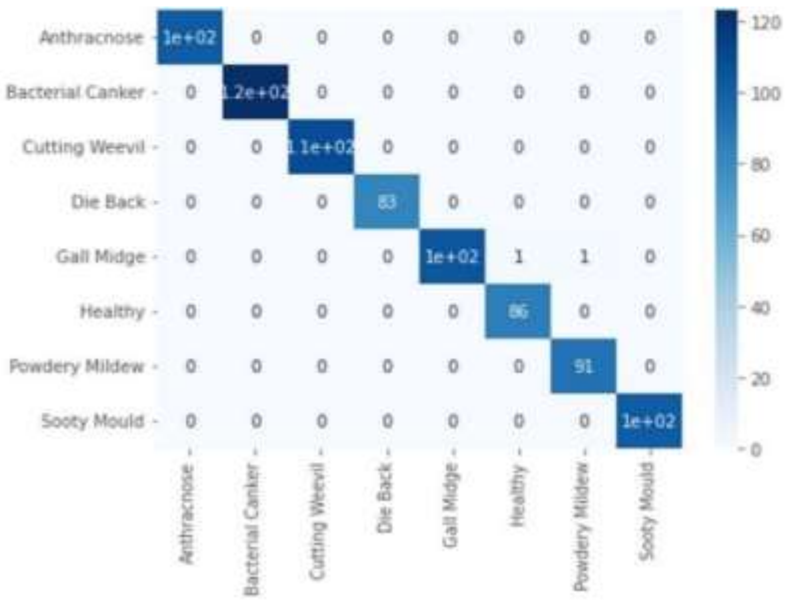

Fig. 1. Confusion Matrix for Mango Leaf dataset

In Table 2. We analyze the performance on the guava leaf dataset. Here also the models performed fairly well with most getting more than 90% accuracy. The best performer was again Densenet201 with data augmentation and fine-tuning giving 98.11% accuracy. As can be observed in the table models performed better after data augmentation and fine-tuning, increasing accuracy by 2-3%.

TABLE II. **PERFORMANCE METRICS FOR THE GUAVA LEAF DATASET**

Base Model	Data Augmentation and Fine Tuning	Dropout	Accuracy	Precision	Recall	F1 score
MobileNetV2	No	0	92.45%	0.92	0.93	0.92
	Yes	0	90.57%	0.9	0.9	0.9
	Yes	0.3	95.28%	0.95	0.95	0.95
InceptionV3	No	0	87.74%	0.87	0.86	0.86
	Yes	0	91.51%	0.91	0.91	0.91
	Yes	0.3	87.74%	0.87	0.87	0.87
Xception	No	0	92.45%	0.92	0.93	0.92
	Yes	0	92.45%	0.91	0.93	0.92
	Yes	0.3	95.28%	0.95	0.95	0.95
Densenet201	No	0	92.45%	0.92	0.92	0.92
	Yes	**0**	**98.11%**	**0.98**	**0.98**	**0.98**
	Yes	0.3	96.23%	0.96	0.96	0.96

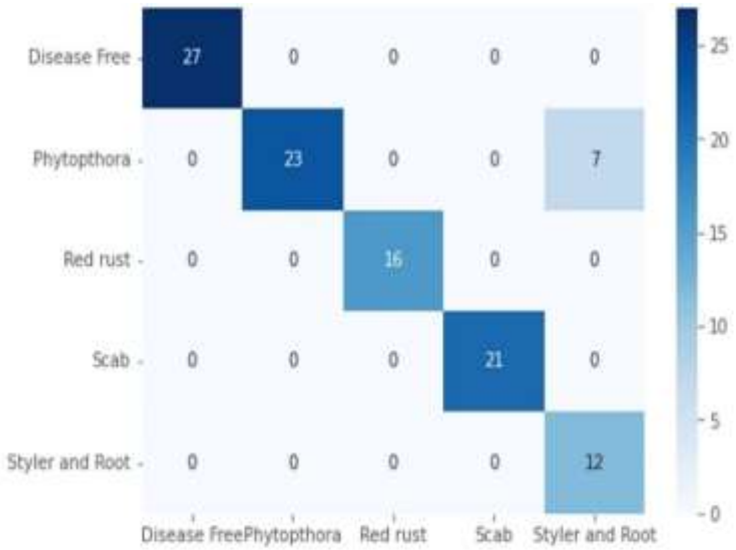

Fig. 2. Confusion Matrix for Guava Leaf dataset

Now let us look at Table III where we compare the performance on the black gram leaf dataset. With a dropout of 0.3, data augmentation and fine-tuning the Densenet201 gave 99.01% accuracy on the test set outperforming all other models. Precision, Recall, and F1 scores were 0.99. The worst performance among all was shown by InceptionV3 with 87.13%. Around a 1-2% increase in accuracy was seen after data augmentation and fine-tuning of the models. Figure 3 shows the confusion matrix where the Densenet201 was able to classify all the disease images correctly in the test set.

TABLE III. **PERFORMANCE METRICS FOR THE BLACKGRAM LEAF DATASET**

Base Model	Data Augmentation and Fine Tuning	Dropout	Accuracy	Precision	Recall	F1 score
MobileNetV2	No	0	97.03%	0.97	0.97	0.97
	Yes	0	91.09%	0.92	0.91	0.91
	Yes	0.3	90.10%	0.93	0.90	0.90
InceptionV3	No	0	91.09%	0.92	0.92	0.92
	Yes	0	87.13%	0.89	0.88	0.88
	Yes	0.3	89.11%	0.89	0.90	0.89
Xception	No	0	94.55%	0.95	0.95	0.95
	Yes	0	96.53%	0.97	0.97	0.97

	Yes	0.3	95.05%	0.95	0.95	0.95
Densenet201	No	0	97.03%	0.97	0.97	0.97
	Yes	0	97.03%	0.97	0.97	0.97
	Yes	**0.3**	**99.01%**	**0.99**	**0.99**	**0.99**

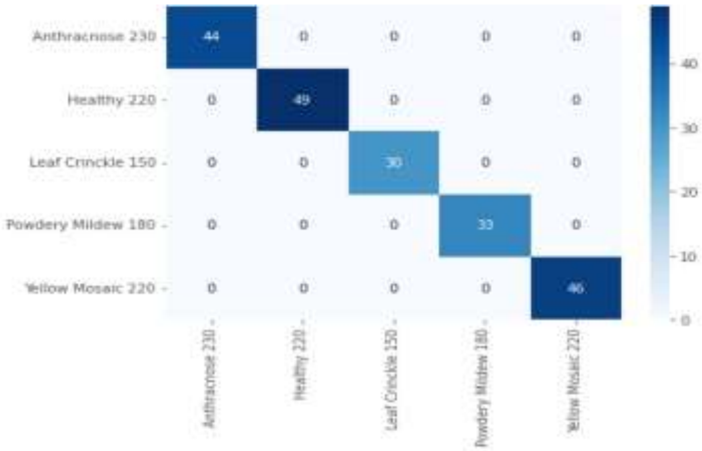

Fig. 3. Confusion Matrix for Blackgram Leaf dataset

Now let's see Table IV for the sugarcane leaf dataset. Denset201 again outperformed other models by giving an accuracy of 96.04% with data augmentation and fine-tuning applied. The worst performance was again given by InceptionV3 with 78.61% accuracy. The images in the sugarcane dataset are not of high quality and thus we can see the accuracy drop in the models' performance. The confusion matrix for the same is given in Figure 4.

TABLE IV. PERFORMANCE METRICS FOR THE SUGARCANE LEAF DATASET

Base Model	Data Augmentation and Fine Tuning	Dropout	Accuracy	Precision	Recall	F1 score
MobileNetV2	No	0	85.74%	0.86	0.86	0.86
	Yes	0	88.12%	0.88	0.88	0.88
	Yes	0.3	87.72%	0.88	0.88	0.88
InceptionV3	No	0	78.61%	0.79	0.79	0.79
	Yes	0	79.41%	0.80	0.79	0.79
	Yes	0.3	79.80%	0.80	0.80	0.80
Xception	No	0	82.57%	0.83	0.83	0.83
	Yes	0	87.92%	0.89	0.88	0.88
	Yes	0.3	87.72%	0.89	0.88	0.88
Densenet201	No	0	90.69%	0.91	0.91	0.91
	Yes	**0**	**96.04%**	**0.96**	**0.96**	**0.96**
	Yes	0.3	95.25%	0.95	0.95	0.95

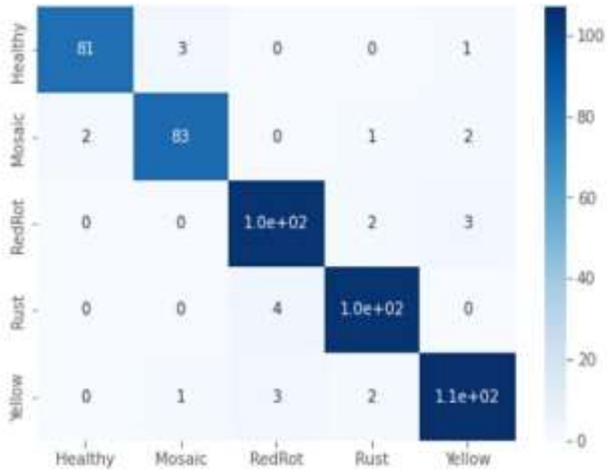

Fig. 4. Confusion Matrix for Sugarcane Leaf dataset

Figures 5, 6, 7, and 8 show some predictions on mango, guava, black gram, and sugarcane datasets respectively using the best-performing models. The true value and the predicted value of the diseases are shown at the top of the images. The green color represents that model has successfully predicted the disease whereas red indicates the model predicted wrong.

Fig. 5. Predictions on the Mango disease dataset

Fig. 6. Predictions on the Guava disease dataset

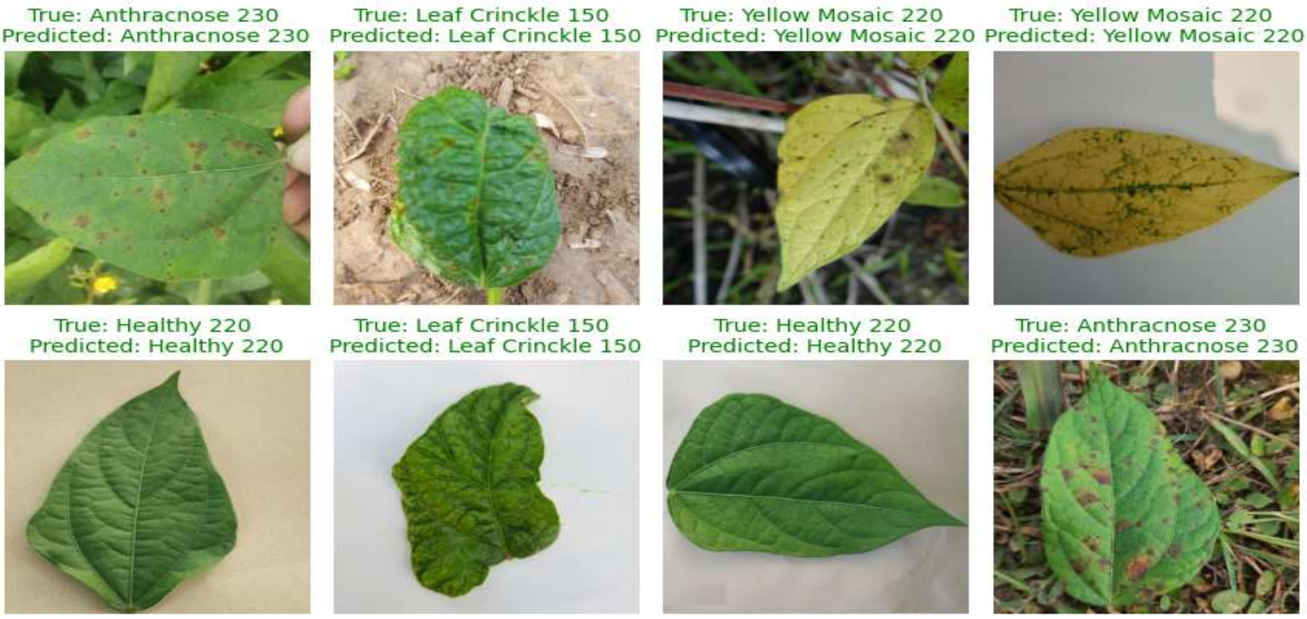

Fig. 7. Predictions on Blackgram disease dataset

Fig. 8. Predictions on Sugarcane disease dataset

5. DISCUSSION

After the results, this can be seen that CNN architectures that are pre-trained are very good at classifying the plant's disease. Easily they can achieve above 90% accuracy. In particular, DenseNet201 performed the best among all the four model architectures used. DenseNet architecture is quite optimized but requires more GPU computation for training. The worst performer was InceptionV3. MobilenetV2 gave a good performance keeping in view it has the least number of parameters among all other models. For mobile devices, we can use this architecture as it has a small size. The Xception model also performed fairly well. Further data augmentation and fine-tuning increased the models' accuracies by around 2-5%. Dropout in a few cases increased the accuracy whereas in others it decreased. Precision, recall, and F1 score were also very high for the used architectures.

5.1.1.1 Comparison with other works

In Table V we can see a comparison of our best models with others on similar plants. In [10] the authors used CCA (Canonical Correlation Analysis) and Cubic SVM (Support Vector Machine) on Mango crops to achieve an accuracy of 95.5%. Authors in [12], [13], [4] used different CNN techniques to get accuracies of 89%, 96.675%, and 96.675%. Our proposed model achieved an accuracy of 99.75% on the mango dataset. In [19] using CNN they achieved an accuracy of 95.61% on Guava whereas our proposed model achieved an accuracy of 98.11%. Authors in [20] achieved an accuracy of 91% using VGG16 and ResNet. In [21] using the Radial SVM technique they achieved 88% accuracy. Our proposed work achieved 96.44% accuracy performing better than the two mentioned before. Using Alexnet, Googlenet, and Resnet authors in [11] achieved an accuracy of 95.86% on black gram crop whereas ours was able to achieve a 99.01% accuracy on the test set. Thus, we can see that our models have performed better as compared to others on similar plant datasets

5.1.1.2 Limitations and future scope

Now let's talk about the limitations of the work presented here. The first one is that the test set was itself created from the dataset and hence the accuracy might drop when models are used in the real world. The other issue is that we have limited images in the dataset, so more data is needed to create better models. More plants with different diseases need to be researched and machine learning and deep learning techniques need to be refined for creating robust models that can be used by farmers to know beforehand what diseases are their crops infected with.

TABLE V. COMPARISON WITH OTHER PLANT DISEASE CLASSIFICATION MODELS

Sno.	Ref.	Model	Accuracy	Plant	No. of diseases	Year
1	[10]	CCA+Cubic SVM	95.5%	Mango	2	2021
2	[12]	ANN, CNN	89%	Mango	3	2020
3	[13]	NNE	80%	Mango	4	2020
4	[4]	Custom CNN	96.675%	Mango	4	2018
5	**-**	**Proposed work**	**99.75%**	**Mango**	**7**	**2023**
6	[14]	Custom CNN	70%	Guava	5	2020

7	[19]	CNN	95.61%	Guava	3	2019
8	**-**	**Proposed work**	**98.11%**	**Guava**	**4**	**2023**
9	[20]	VGG-16, ResNet	91%	Sugar cane	5	2022
10	[21]	Radial SVM	88%	Sugar cane	2	2023
11	**-**	**Proposed work**	**96.04%**	**Sugarcane**	**4**	**2023**
12	[11]	AlexNet,GoogleNet, Resnet50	95.86%	Black gram	1	2022
13	**-**	**Proposed work**	**99.01%**	**Black gram**	**4**	**2023**

6 CONCLUSION

In this study, we have tried to find the best-performing models on the four different plant leaf disease datasets: Mango, Guava, Sugarcane, and Black gram. We used MobileNetV2, InceptionV3, Xception, and Densenet201 model architectures that were pre-trained on ImageNet. Further, the effect of data augmentation techniques, fine-tuning, and dropout was also studied. Our findings show that the suggested strategy is effective in classifying images of different plant diseases with high accuracy, precision, recall, and f1 score on the test set. According to our research, the Densenet201 performed the best among all other models in all datasets we used. Data augmentation and fine-tuning also helped in increasing the accuracies of the models but dropout only increased accuracy in a few cases, in others it reduced the accuracy. We also compare models with those mentioned in other studies and find our models outperformed them in most of the cases. Hence using pre-trained models and then fine-tuning them can give high accuracies even in a difficult task like classifying plant diseases. This also saves a lot of time and resources since the networks don't need to be trained from scratch and can be modified accordingly.

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